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Patient Prognosis based on Lung Nodule Detection: A Review and Prediction Using Machine Learning and Deep Learning Techniques

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Abstract: Lung Cancer Integrating Pathological and Radiological Features is a strong and descriptive title that effectively communicates the core aspects. It emphasizes the fusion of different data sources using a neural network approach for the purpose of understanding and predicting lung cancer outcomes. It's clear and concise, which is ideal for a project title. In this study, we provide a summary of the latest CAD methodologies that use deep learning to pre-process, segment, classify, and retrieve lung nodule data from CT scans, in addition to reduce false positives. Up to November 2020, academic conferences and publications were the source of a selection of articles. We go over the history of deep learning, go over some key points about lung nodule CAD systems, and evaluate the effectiveness of the chosen research over a range of datasets. Researchers and radiologists are able to acquire a better understanding of computer-aided design machine learning as well as deep learning methods for the detection, segmentation, classification, and retrieval of pulmonary nodules by reading this review. We review the effectiveness of existing methods, discuss their drawbacks, and suggest future lines of investigation for high-impact research.

1. INTRODUCTION

One of the primary causes of cancer-related fatalities globally is still lung cancer, and improving patient outcomes largely depends on early diagnosis and prognosis. New developments in deep learning (DL) and machine learning (ML) approaches have demonstrated encouraging outcomes in assisting the identification of lung nodules from medical imaging data. With the use of ML and DL algorithms, this paper attempts to present an overview of the state-of-the-art approaches for predicting patient prognosis based on lung nodule identification. We do a thorough analysis of the most current research on this subject, paying particular attention to the approaches, datasets, performance indicators, and difficulties faced. We also go over possible avenues for future research and development to improve the precision and clinical use of these prediction models.
Lung cancer remains a significant global health challenge, necessitating improved methods for early detection and prognosis prediction. Machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for analyzing medical imaging data, particularly in the context of lung nodule detection. By leveraging these techniques, researchers have made significant strides in predicting patient prognosis based on features extracted from detected lung nodules. In this review, we explore the recent advancements in this field, aiming to provide insights into the methodologies, challenges, and future prospects.

Attention mechanisms allow the model to focus on specific parts of the input sequence while making predictions. You can incorporate attention mechanisms within residual blocks to capture more context and improve performance. For example, you can add self-attention layers within the residual blocks to enable the model to weigh the importance of different features at different spatial positions or time steps.
Attention in Transfer Learning: When combining transfer learning with attention mechanisms, you can fine-tune a pre-trained model with attention layers added to it. This allows the model to adapt its attention patterns to the specific features of your task. Attention mechanisms can be particularly useful when dealing with tasks where specific parts of the input are more relevant than others, such as in image captioning or natural language processing tasks.
Custom Architectures: Designing custom architectures that combine residual blocks, attention mechanisms, and transfer learning is also an option. You can experiment with different combinations of these techniques to find the best architecture for your specific task.
For example, you might have residual blocks in the early layers of your network for feature extraction, attention mechanisms in the middle layers for capturing relevant information, and then additional residual blocks for fine-tuning and classification.

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Hybrid Models: You can also consider using a hybrid model where you have multiple branches of the network, each utilizing different techniques. For instance, one branch can be a residual network, another branch can use attention mechanisms, and then the outputs can be combined or concatenated in some way. Remember that the effectiveness of these combinations depends on the specific task and dataset. It's recommended to experiment with different configurations and conduct thorough evaluations to determine the optimal combination for your use case.

2. LETERATURE SURVEY

We have examined a few of the papers to see how their suggested approaches were put into practice. Which data collection they have utilised, along with the size guidelines and techniques they employ. We examined their shown accuracy. similar to Lung Nodule Analysis 2016's Lung Nodule Classification on Computed Tomography Images Using Fractalnet LUNA 16. There are 888 low-dose lung CT scans in the LUNA 16 dataset. The data set's size is There are 551,065 annotations in the dataset overall.

S.No	Title of the Paper	Journal Name	Dataset Name	Size	Methodology Used	Accuracy
1	Lung Nodule Classification on Computed Tomography Images Using Fractalnet	Wireless Personal Communications (2021) 119:1209–1229 https://doi.org/10.1007/s11277-021-08258-w	LUNA 16 (LUng Nodule Analysis 2016). LUNA 16 dataset contains 888 low-dose lung CTs,	The dataset has a total of 551,065 annotations.	used both Adam and SGD((Stochastic Gradient Descent)) optimizer to train our network. Fractalnet model	Adam: 86.30 SGD: 90.41 The Fractalnet model has an accuracy of 94.79%, specificity of 90.41% and sensitivity

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						of 96.68% which is comparatively better than rest of the network compared with it.
2	Lung cancer detection from CT scans using modified DenseNet with feature selection methods and ML classifiers	Expert System with Applications.	DensNet201, DenseNet201 extracted features, ETCselected features, MRMR selected features and combined ETC with MRMR chosen features.		Convolutional neural networks (CNNs) andstate-of-the-art pre-trained transfer learning (TL) models, such as VGG16, DenseNet201	The proposed system achieved a high accuracy of 100%, an averageaccuracy of 95%, and a p-value of less than 0.001 after applying a 5-fold method.
3	Deep feature selection using adaptive -Hill Climbingaided whale optimization algorithm for lung and colon cancer detection.	Biomedical Signal Processing and Control	LC25000 dataset	25000	hybrid meta-heuristic optimization algorithm, AdBet-WOA (Whaleoptimization algorithm with integrated Adaptive -Hill Climbing local search), utilizing which the SupportVector Machine (SVM)	accuracy of 99.99%, 99.97%, and 99.96%, respectively,

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4	Medical image analysis based on deep learning approach.	Multimedia Tools and Applications	Radiography, endoscopy, Computed Tomography (CT), Mammography Images (MG), Ultrasound images, Magnetic Resonance Imaging (MRI), Magnetic Resonance Angiography (MRA), Nuclear medicine imaging, Positron Emission Tomography (PET) and pathological tests.	deep CNN trained and evaluated on over 1,000,000 mammogram images for breast cancer screening exam classification. Conant et al. [26] developed a Deep CNN based AI system to detect calcified lesions and soft- tissue in digital breast tomosynthesis (DBT) images. Kang	CNN, RNN, An LSTM	Comparison Only A

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				et al. [62] introduced Fuzzy completely connected layer (FFCL) architecture, which focused primarily on fused fuzzy rules with traditional CNN for semantic BI-RADS scoring. The proposed FFCL framework achieved superior results in BI-RADS scoring for both triple and multi-class classifications.		
5	Enhanced Whale Optimization Algorithm with Wavelet Decomposition for Lithium Battery Health Estimation in Deep Extreme Learning Machines	Applied Science	NASA dataset	Used : (a) CS-35; (b) CS-36; (c)CS-37;	wavelet decomposition; whale optimization algorithm; deep extreme learning machine	absolute correlation coefficients exceeding 98%.

				(d) CS-38.		
6	Detection of Liver Tumour Using Deep Learning Based Segmentation with Coot Extreme Learning Model	Biomedicine	3DIRCADb 1 dataset	We used the CT scan pictures from 20 patients found in the 3D-IRCADb1 database, which represents 75% of the tumours in that collection.	tumour prediction; coot optimization algorithm; extreme learning model; deep learningbased interactive segmentation; intensity levels	the existing technique has 70.7% and the proposed model has 77.54%.
7	Efficient feature selection using one-pass generalized classifier neural Network and binary bat algorithm with a novel fitness function.	Methodologies And Application	Data Set: 1. UCI data, 2. publicly available microarray datasets (Dua and Casey 2017; Zhu et al. 2007). 3. The	wdbc dataset, i.e., 32.47%, 62.47% and 7.71% better in comparison with RBFNN, PNN and ELM, respectively. In the case of ILDP dataset, OGCNN performs 4.75%	Binary Bat algorithm along with One-passGeneralized Classifier Neural Network (OGCNN). OGCNN has shown to be providing faster classification than	Ovarian cancer dataset PNN performed better than OGCNN, RBFNN and ELM by 14.03%, 45.30% and 10.76%, respectively. The Leukemia dataset

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			datasets from UCI repository are Breast Cancer Wisconsin Diagnostic (wdbc), 4. Indian Liver Patient Dataset (ILDP) and 5. Ionosphere.	, 5.94% and 0.85% better than RBFNN, PNN and ELM, Respectively.	Generalized Classifier Neural Network (GCNN), Logarithmic learning GCNN (LGCNN), Extreme Learning Machine (ELM) and Radial Basis FunctionNeural Network (RBFNN) (Ozyildirim and Avci 2016)	recorded the best performance for OGCNN, i.e., a f-score of 1. OGCNN performed better than RBFNN, PNN and ELM by 1.42%, 48.42% and 15.44%, respectively,
8	Lung cancer detection from CT scans using modifiedDense Net with feature selection methods and MLclassifiers.	Expert Systems with Applications	Frameworks : compare the performance of modified DensNet201, DenseNet201 extracted features, ETCselected features, MRMR selected features and combined ETC with MRMR chosen features.		Machine Learning and Deep Learning Techiques.	The proposed system achieved a high accuracy of 100%, an averageaccuracy of 95%, and a p-value of less than 0.001 after applying a 5-fold method.
9	Extreme Learning Machine Framework for	Image and Signal Processing	Dataset: the K10 cross validation		Extreme	ELM showed an

	Risk Stratificationof Fatty Liver Disease Using Ultrasound Tissue Characterization.		protocol on S8 data set,		Learning Machine (ELM)-based tissue characterization system (a class of Symtosis) for risk stratification of ultrasound liver images. ELM is used to train single layer feed forward neural network (SLFFNN).	accuracy of 96.75% compared to 89.01% for SVM, and correspondingly, the AUC: 0.97 and 0.91, respectively. Further experiments also showed the mean reliability of 99% for ELM classifier, along with the mean speed improvement of 40% using ELM against SVM. We validated the symtosis system using two class biometric facial public data demonstrating an accuracy of 100%.

10	Wrapper-based optimized feature selection using nature-inspired algorithms	ORIGINAL ARTICLE	the University of California at Irvine (UCI) database	PSO is a swarm-based technique proposed by Kennedy and Eberhart [54]. Various properties of PSO are its fast convergence rate, few parameters'	the performance of BPSO have been studied. A proper fitness function with well-known data set from the UCI repository has been implemented using MATLAB, and for classification, the K-NN classifier has been used.	Numerous natures inspired metaheuristic techniques like BFO (Bacterial foraging optimization), PSO (particle swarm optimization), GA (genetic algorithm), BA are there which aid in building a good classifier to solve these kinds of optimization problems [12, 13].
11			The UK Biobank resource (UKBB) is a prospective cohort study of over 500,000 UK residents recruited during 2006–2010 from age 40	The total number of participants was 501,839, with 2643 lung cancer cases during the follow-up period.	fitted flexible Royston-Parmar (R-P) proportional hazards models with time since attending	C-index:

	The value of blood-based measures of liver function and urate in lung cancer risk prediction: A cohort study and health economic analysis	Cancer Epidemiology	years [26]. Blood samples were collected at baseline from all participants and included the blood tests evaluated in the present study (Table S1).			95 %CI:0.794–0.816. Expanding to include blood measurements increased the c-index to 0.815 (95 %CI: 0.804–0.826;p < 0.0001; FNI:0.06). Expanding to include FEV1, alcohol status, and waist circumference increased the c-index to 0.811 (95 %CI: 0.800–0.822;p < 0.0001;FNI: 0.04). The c-index for the fully expanded model containing all variables was 0.819 (95 %CI:0.808–0.830;p < 0.0001;FNI:0.09).

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				After excluding missing data, 412,862 participants (2116 events) were available to identify the blood measurements' functional forms and 439,863 (2050) for FEV1.		
12	Eye-tracking to find missed Lung Nodules	New Proposeal	Max Rosen, University of Massachusetts Chan Medical School Federico Sorcini, University of Massachusetts Chan Medical School Alexander Bankier, University of Massachusetts Chan Medical School		diagnosing from a radiological image	Eye-tracking during diagnostic visual search shows that radiologists make recognition errors

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13	Application of digital pathology and machine learning in the liver, kidney and lung diseases	Journal of Pathology Informatics	WSI technologies andmachine learning have seen effective applications in histological analysis of hepatic tissue to help evaluate and treat various diseases such as Non-Alcoholic Fatty Liver Disease (NAFLD	elastin fibers in WSIs of Elastica van Gieson-stained liver biopsy specimens from 289 NAFLD patients across multiple hospitals.	paired with various ML and DLNN algorithms, AI will be able to analyze the WSI images, extract disease-relevant information and make diagnoses objectively.	The results showed an accurate separation of the large lipid droplets and small lipid droplets with a 93.7% specificity and 99.3% sensitivity and a good correlation (R2=0.97) with the manual assessment by pathologist.
14	Improving detection of cystic fibrosis	*HELIYON*	elastin fibers in WSIs of Elastica van Gieson-stained liver biopsy	predicating CFLD in 10 of 32 patients (31%).	LSM and predicted CFLD.	LSM can be used as a surrogate for PHT in patients with cirrhosis (26). A cut-off of 6.85kPa

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	related liver disease using liver fibrosis assessment tools		specimens from 289 NAFLD patients across multiple hospitals.			had a sensitivity of 77% and specificity of 89% for diagnosing PHT in CFLD

CIFAR-10 Dataset
110 layers on the residual network have the same order of parameters as the previous network, only 19 layers. With a deeper network, it outperformed the previous network. However, with a 1202-layer network, the error increased.

3. PROPOSED SYSTEM

Using ML and DL approaches for lung nodule identification, we do a thorough evaluation of recent research on prognostic prediction for patients. We divide the methods into two categories: deep learning (DL) techniques like convolutional neural networks (CNN) and recurrent neural networks (RNN), and classic machine learning (ML) approaches like support vector machines (SVM) and random forests (RF). We analyze the model designs, training tactics, feature extraction techniques, and preprocessing stages used in these investigations.

Datasets and Performance Metrics: Public repositories and institution-specific collections of medical imaging data are among the datasets that we examined in the evaluated research. We also go over the performance measures, such area under the receiver operating characteristic curve (AUC-ROC), sensitivity, specificity, and accuracy, that were used to assess the prediction models.

Misses are the most common and serious error in diagnostic visual search and have been investigated extensively with eye-tracking. For experienced radiologists, misses are different than for non-experts in a significant way. Eye-tracking during diagnostic visual search shows that radiologists make recognition errors (where missed abnormalities are still looked at longer than normal tissue but below some arbitrary threshold for conscious recognition. Experts make these recognition errors across modalities and anatomy, including lung nodules in chest CTs. A critical need is characterizing these non-conscious processes in diagnostic visual search and utilizing these non-conscious processes to improve nodule detection beyond conscious detection limits. We reviewed some of references to determine why errors are made when diagnosing from a radiological image. Specifically, we want to know whether misses occur because Radiologists don't look at the region in the image that has an abnormality. In addition, we would like to use the eye-movement data to see if deep machine learning can use the eye-movement data to learn if an abnormality is present in the images.

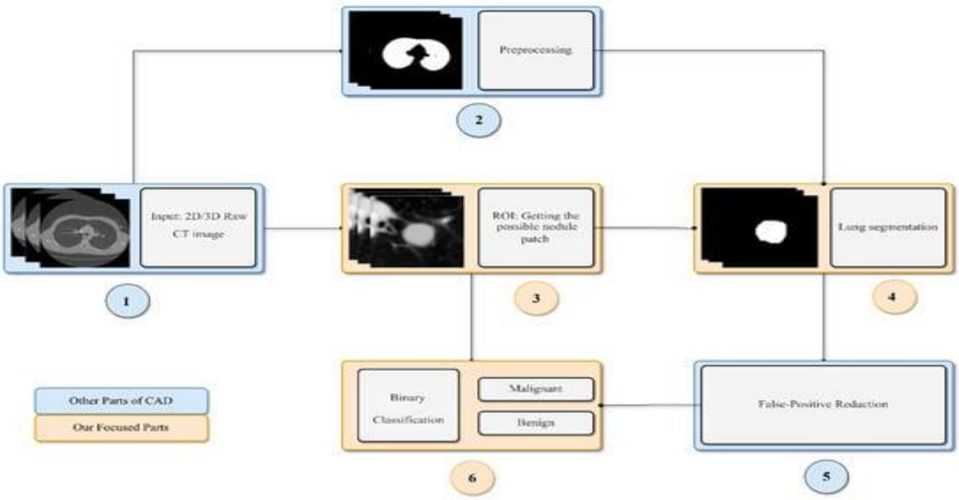

Figure-1:Proposed Methodology Working Process.

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Comparing the results of predicting patient prognosis based on lung nodule detection using machine learning and deep learning techniques involves several steps:

Define Evaluation Metrics: Determine the metrics that are most relevant for evaluating the performance of your models. Common metrics for binary classification tasks like predicting patient prognosis include accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve (AUC-ROC), and area under the precision-recall curve (AUC-PR).

Split Data: Divide your dataset into training, validation, and test sets. The training set is used to train the models, the validation set is used to tune hyperparameters and monitor performance during training, and the test set is used to evaluate the final performance of the models.

Training Models: Train machine learning and deep learning models using the training data. Ensure that you use appropriate techniques for preprocessing, feature engineering, and model selection.

Hyperparameter Tuning: Use the validation set to tune the hyperparameters of your models. This might involve adjusting learning rates, batch sizes, network architectures, regularization techniques, etc.

Evaluate Performance: Evaluate the performance of your models on the test set using the evaluation metrics defined earlier. Compare the performance of different models based on these metrics.

Statistical Significance: Determine if the differences in performance between the models are statistically significant. This can be done using hypothesis testing techniques such as t-tests or cross-validation paired tests.

Clinical Relevance: Consider the clinical relevance of the results. While one model may perform better according to certain metrics, it's important to assess whether these improvements are meaningful in a clinical context.

External Validation: If possible, validate the models on an external dataset to assess their generalizability.

Interpretability: Consider the interpretability of the models. Deep learning models may offer superior performance but lack interpretability compared to simpler machine learning models like decision trees or logistic regression. Reporting: Clearly report the results of your comparison, including the performance metrics, any statistical tests conducted, and any limitations of the study.

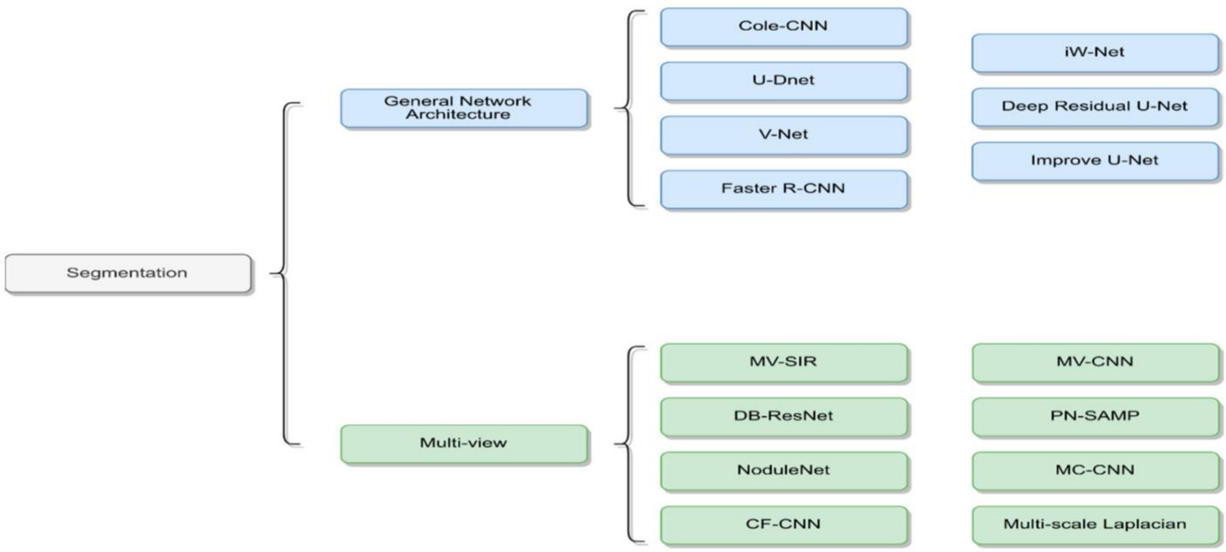

Figure.2: Deep learning models may offer superior performance procedure.

Many research studies have proposed new architectures by taking multiple views of lung nodules as inputs to neural networks to achieve improved results [53, 66,67,68,69,70]. These segmentation methods are primarily based on CNN networks and combine multiscale or multiview methods to train the neural networks. The structures of the different networks are depicted in Figure 2.

Generally, lung nodules that are close to blood vessels and pleura are most challenging to detect. Thus, increasing the detail of the boundary nodules is core for all models. Pezzano et al. [**65**] proposed a network structure based on

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U-Net to segment lung nodules. The authors developed the multiple convolutional layers (MCL) module to fine-tune the details of the boundary nodules and post-process the nodule segmentation results. Morphological methods were used to strengthen the detail of the edge nodules. Dong et al. [**67**], meanwhile, proposed a model that incorporated features of voxel heterogeneity (VH) and shape heterogeneity (SH). VH reflects differences in gray voxel value, while SH reflects the characteristics of a better nodule shape. The authors found that VH can significantly learn gray information, whereas SH can better learn boundary information.

RESULTS AND DISCUSSION

As we have read many research article, which they were used many data sets and different data sets have given different results with accuracy. Here we have used ImageNet Data Set and results of the data set and how was its Layers working procedure will be considered.

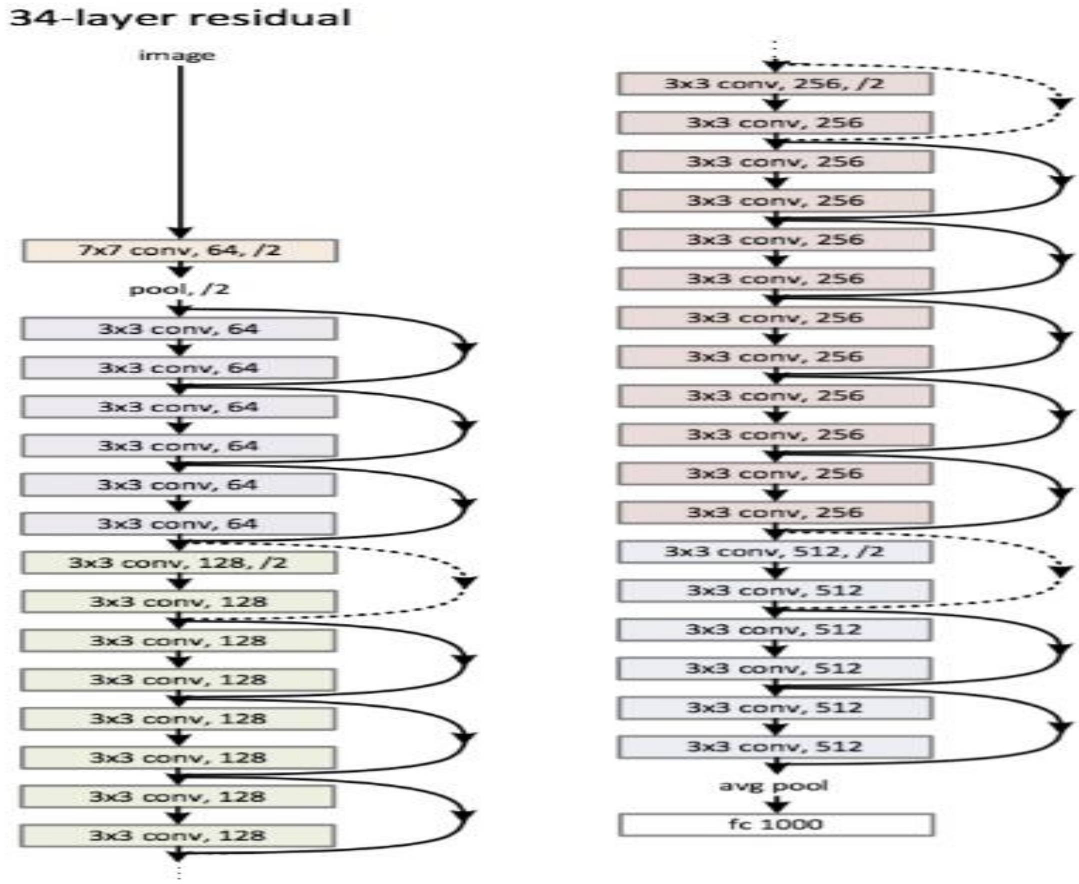
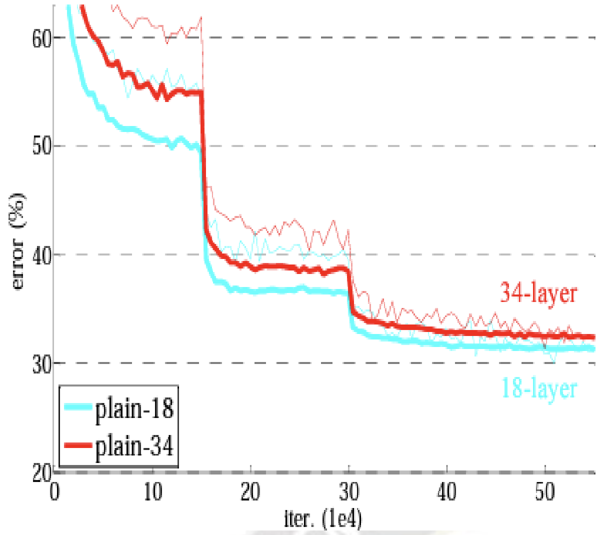
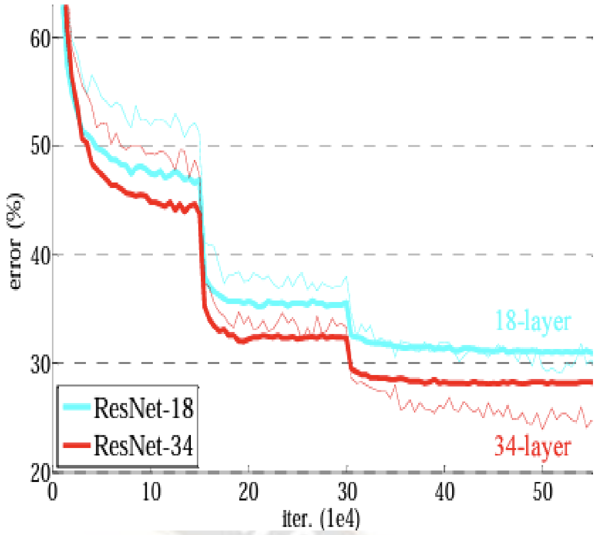


Figure.3: 34- The layers have the same filters for the same feature map size of the output.

ImageNet Dataset results:

The ImageNet dataset is a large-scale dataset used for training and evaluating image classification algorithms. It consists of millions of labeled images across thousands of categories. When researchers evaluate their models using the ImageNet dataset, they typically report metrics such as top-1 and top-5 accuracy. Top-1 accuracy refers to the percentage of images for which the correct label is the model's most confident prediction. Top-5 accuracy refers to the percentage of images for which the correct label is among the model's top 5 most confident predictions. State-of-the-art models achieve very high accuracies on the ImageNet dataset. For example, models based on convolutional neural networks (CNNs) have achieved top-1 accuracies of over 85% and top-5 accuracies of over 95%.





- Training and validation error is higher in deeper networks, 34-layered, than in 18-layered.
- With the introduction of residual networks, 34-layer with residual connection has much lower training and validation error than 18-layer.
- Resnet 34 performed better than the Resnet 18 network with the same number of layers as in the plain network.
- Resnet-34 performed well in generalizing validation data and showed less errors.

CONCLUSION

The ImageNet dataset has been instrumental in advancing the field of computer vision, particularly in the area of image classification. Here are some key conclusions drawn from the results obtained using the ImageNet dataset:
The project on the detection and classification of diabetic retinopathy using Generative Adversarial Networks (R-CNN), V-U Net, V-Net represents a significant step forward in leveraging advanced technologies for early diagnosis and management of a critical diabetes-related eye disease. The historical reliance on manual examination by ophthalmologists is being transformed by the potential of artificial intelligence and CNN to enhance the efficiency and accuracy of diabetic retinopathy detection. The use of GNA(General Network Architecture in medical imaging offers a unique advantage by generating realistic and diverse retinal images, addressing the challenges associated with limited and variable datasets. The project successfully demonstrates the ability of to augment datasets and improve the robustness of machine learning models, particularly in capturing subtle patterns indicative of early-stage diabetic retinopathy. This approach not only aids in the detection of the disease but also facilitates the classification of its severity, enabling tailored treatment plans for affected individuals.

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